

# **The Influence of Redundant Spatial Regularities in Statistical and Sequence Learning**

by

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### **Author's Declaration**

I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners. I understand that my thesis may be made electronically available to the public.

## **Abstract**

The following two studies examined the influence of spatial regularities on our ability to learn and predict frequencies and sequences of events. Research into statistical and sequence learning has demonstrated that we can learn the statistical properties of events and use this knowledge to make predictions about future events. Research has also demonstrated that redundant spatial features associated with events can influence our ability to respond to and discriminate between different stimuli. The goal of this thesis was to test whether redundant spatial features could influence our ability to notice non-spatial regularities in an environment. Using a computerized version of the children's game 'rock-paper-scissors' (RPS), undergraduates were instructed to win as often as possible against a computer that played varying strategies. For each strategy, the computer's plays were either presented with spatial regularity (i.e., 'rock' would always appear on the left of the screen, 'paper' in the middle, and 'scissors' on the right) or without spatial regularity (i.e., the items were equally likely to appear in any of the three screen locations). The results showed that, although irrelevant to the task itself, spatial regularities had a moderate influence when participants learned to exploit easy strategies, and a more pronounced influence when learning to exploit harder strategies. This research suggests that redundant spatial features can influence our ability to learn and represent distributions of events.

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## CHAPTER 1: Introduction

We have an amazing ability to process and categorize events into coherent patterns of observation. This skill is crucial to learn the properties that make up our environment and to enable successful interaction with that environment. Our experiences while driving a car provide information about how much to press the gas and brake pedals for gradual (rather than jerky) accelerations and decelerations, our experiences with the food at a cafeteria give information about which days of the week provide the best meals, and a batter's experiences with a pitcher's throwing patterns can help him/her predict what pitch to expect after seeing two fastballs and a change-up.

Although we may only pay attention to some specific features of an event to help us learn its properties, there may potentially be additional features related to the event that can provide equally predictive information. A pilot attempting to learn the sequence of button presses necessary for takeoff in a particular aircraft can learn either the sequences of buttons that need to be pressed, or simply learn the spatial arrangement of the buttons, without necessarily relying on their functions. Previous research has demonstrated that both task relevant information (e.g., in the pilot example, the function of each button) and task irrelevant information (e.g., the *spatial* sequencing of button presses) can have an influence on our behaviour. Less is known about the potential learning benefits that can occur when two or more event properties converge. The goal of this thesis is to explore the potential benefits that multiple features can have on our ability to learn and perceive regularities in our environment.

There is a large body of research that attests to our ability to extract patterns and regularities from our environment. Participants can learn long, sometimes complex motor

sequences through trial and error alone (Jenkins, Brooks, Nixon, Frackowiak, & Passingham, 1994; Jueptner, Stephan, Frith, Brooks, Frackowiak, & Passingham, 1997a, b; Toni, Krams, Turner, & Passingham, 1998) and this type of learning can occur outside of explicit awareness (Willingham, 1999; Willingham, Wells & Farrell, 2000). We are also sensitive to the statistical properties that compose specific events. Studies exploring language acquisition have shown that we can learn to segment words from an artificial language based solely on the transitional probability between the syllables that compose the language (Saffran, Newport, & Aslin, 1996; see Ellis, 2002 for review). This ability has also been demonstrated using non-word auditory stimuli (Creel, Newport, & Aslin, 2004) and visual stimuli (Fiser & Aslin, 2001; Orban, Fiser, Aslin, & Lengyel, 2008; Abla & Okanoya, 2009).

This research demonstrates that under certain conditions, we are proficient at detecting patterns and regularities in the environment; however, in real world situations, events do not always occur with absolute certainty. Indeed, uncertainty poses a difficult problem to overcome when attempting to understand the rules underlying a series of events. Yu and Dayan (2005) describe two different types of uncertainty that can be associated with events. *Expected* uncertainty describes an environment in which the probability of an event occurring is known, but its predictability is stochastic and unreliable (e.g., the probability of a coin flip resulting in 'heads' is 0.5, but it is uncertain whether 'heads' will come up on the next trial). *Unexpected* uncertainty describes perceived events that violate expectations associated with an environment (e.g., a coin that flips to 'tails' on 95/100 trials; Yu & Dayan, 2005).

Studies looking at probabilistic learning have explored our ability to learn under uncertain conditions. The extensive research on probability matching has demonstrated that we are generally able to represent the expected uncertainty of an environment and approximate our predictions of outcomes based on their probability of occurrence (Vulkan, 2000; Shanks, Tunney, & McCarthy, 2002). We are also sensitive to situations of unexpected uncertainty, where the events we perceive do not match our expectations. Danckert and colleagues (2012) had healthy and brain damaged subjects play the children's game 'rock-paper-scissors' against a computer that switched from choosing all three items with equal probability, to choosing one item ('paper') on 80% of trials. Healthy subjects managed to notice this switch and adapt their play (i.e., prefer 'scissors') to increase their win rate (Danckert et al., 2012).

Studies examining multiple-cue probability learning also suggest that we can learn to use task-relevant redundant cue features to predict events (Edgell et al., 1996; Edgell & Morrissey, 1992; Edgell & Castellan, 1973). Edgell and Morrissey (1992) presented participants with cues made up of multiple features (e.g., a geometric shape made up of horizontal or vertical lines) before asking them to predict whether a green or red light would appear. Through trial and error, participants learned to associate cues with different outcomes. The researchers varied the predictability of the cues so that in certain conditions only one cue feature would predict the light that would appear (e.g., horizontal lines, regardless of the geometric shape, would predict a green light), or that both features together would serve to predict which light would appear (e.g., a triangle made up of vertical lines would predict a green light). Results showed that participants in both conditions managed to learn to associate the predictive cues with event outcomes (Edgell &

Morrissey, 1992). This research shows that participants can learn to associate *task-relevant* redundant features of a cue with future events, and selectively ignore other features when they are not relevant to the prediction.

These examples demonstrate that we are able to learn the regularities associated with events in the environment, and that we are also able to do so when the rules underlying these events are not entirely certain. These data also demonstrate that this learning is flexible and can adapt to environmental changes. However, the primary focus of this prior research has been to understand how events related specifically to a task are perceived and integrated. In reality, events can have many redundant features that may help (or hinder) our ability to learn the rules associated with them.

Research has shown that the *task-irrelevant* or redundant features can influence performance on certain tasks. Perhaps the dominant example of how irrelevant or redundant information can influence performance comes from work showing *interference* effects. For example, research on the Simon effect has shown that we are faster to respond to targets when their location is congruent with the location of the response (Simon, 1969; see Hommel, 2011 for review; see also MacLeod, 1991 and Lu & Proctor, 1995 for a review of other interference effects). In contrast, redundant information has also been shown to *improve* performance. Druker and Anderson (2010) had participants perform a simple colour discrimination task (i.e., determine whether a target was red or green). They then manipulated the probability with which targets would appear in a specific region of the display. Although the spatial distribution of targets (i.e., with targets primarily occurring within a 'hotspot' on the screen) was irrelevant to the task, results showed that both speed and accuracy for the colour discrimination was improved at the high probability location.

This was true even though participants were not specifically instructed to pay attention to a target's location and despite the fact that most participants were unaware of the biased distribution of target locations (Druker & Anderson, 2010). Both of these examples demonstrate that the spatial features of a stimulus (and in the case of the Simon effect, its associated response codes) can influence our ability to categorize and respond to targets, even when such spatial information is not directly related to the task. However, less is known about the influence of redundant spatial features on our ability to learn the distributions of events.

The aim of the current study was to explore the possibility that redundant spatial information would improve our ability to learn the properties associated with a non-spatial task. Furthermore, it was hypothesised that redundant spatial information would make it easier to detect changes occurring in the non-spatial task. Through the use of a computer game, this study demonstrated that spatial regularities can have an influence on learning, but that its effects may serve primarily as an aid when such learning is more difficult.

## CHAPTER 2: Experiment 1

In the first experiment, participants played the classic children's game 'rock-paper-scissors' to measure how well they could learn to exploit a bias in their opponent's play strategy (e.g., the computer chooses 'rock' most of the time) when that bias was presented under conditions of spatial regularity (i.e., specific choices always presented in specific spatial locations) or no spatial regularity (i.e., play choices presented in random spatial locations; Figure 1). The goal was to determine whether spatial regularity associated with stimuli, but irrelevant to the task itself, would improve a participant's ability to detect and exploit a computer's strategy. This task was also designed to understand whether spatial regularity could improve a participant's ability to detect *changes* in a computer's play and switch his/her play accordingly (i.e., would it be easier to detect an opponent's shift from biasing 'rock' to now biasing 'scissors' when that information was presented with redundant spatial regularity?).

In this version of 'rock-paper-scissors' (RPS), participants were either assigned to a *regularity* condition, where the location of the computer's choices would remain constant for each item, or a *no regularity* condition, where the location of the computer's choices were not related to the computer's strategy. If spatial regularities assist a participants' ability to learn and detect changes in a series of events, participants in the regularity condition would be expected to exploit their opponent's bias more efficiently than those in the no regularity condition. Furthermore, when the computer switches from one strategy to another, the addition of spatial regularity in the task should enable a more rapid or efficient switch to the second strategy when contrasted with participants in the no regularity condition.

## 2.1 Methods

### *Participants*

Thirty-nine undergraduates (19 female, Mean age = 19.8 years, SD = 1.7 years) from the University of Waterloo participated in this experiment for course credit. The experimental protocol was approved by the University of Waterloo's Office of Research Ethics and all participants gave informed written consent prior to participation.

### *Display and Keyboard*

All stimuli were presented on an 18" ViewSonic Professional Series PF790 Cathode Ray Tube monitor at a resolution of 1280x1024 with refresh rate set to 85 Hz. Responses were recorded using a Dynex DX-WKBD keyboard.

### *RPS Game Play*

In a normal RPS game, players face each other and, on the count of three, reveal their choice of either rock, paper, or scissors, using hand gestures. In this game, 'rock' beats 'scissors' by crushing it, 'scissors' beats 'paper' by cutting it, and 'paper' beats 'rock' by wrapping it up. In the task, participants played a computerized version of RPS programmed using the PsychoPy library (Pierce, 2009). Pictures of a rock, paper, and scissors were presented to participants throughout the task to simplify the interpretation of each item.

Participant sat approximately 60cm away from the screen throughout the task. Each trial started with four equally sized squares displayed on a grey background. Three of the squares were horizontally aligned 1.9° of visual angle above the centre of the screen and

spaced 3.8° apart, with one square in the left portion of the screen, one in the middle, and one on the right. The last square was vertically aligned with the top middle square and located 1.9° below the centre of the screen. Each square was 6.7° x 6.7° (Figure 1).

At the start of each trial all four squares were presented in blue. After 500ms, the top three squares changed colour to pink to indicate that the computer had made its choice. Participants would then make their selection by pressing the 'left' arrow key for rock, the 'down' arrow key for paper, and the 'right' arrow key for scissors. Once they made their choice, the computer's choice would appear in one of the top three squares while the participants' choice would appear simultaneously in the bottom square. The screen's background would turn green if the trial resulted in a win for the participant, red for a loss, and would remain grey for a tie. The result would be displayed for 1000ms before starting the next trial (Figure 1a).

Participants were assigned to one of two spatial regularity conditions:

- 1) *Regularity*: the computer's choices would always appear in the same respective squares (i.e., 'rock' would always appear in the top left square, 'paper' would always appear in the top middle square, and 'scissors' would always appear in the top right square)
- 2) *No regularity*: The computer's choices would appear randomly in one of the three top squares on each trial (Figure 1b).

In each condition, participants were exposed to three stages of trials:

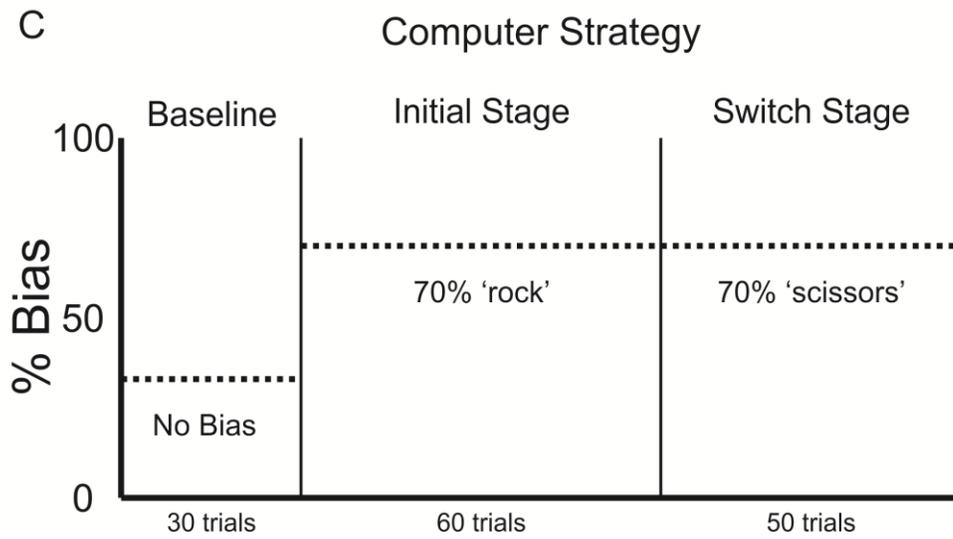
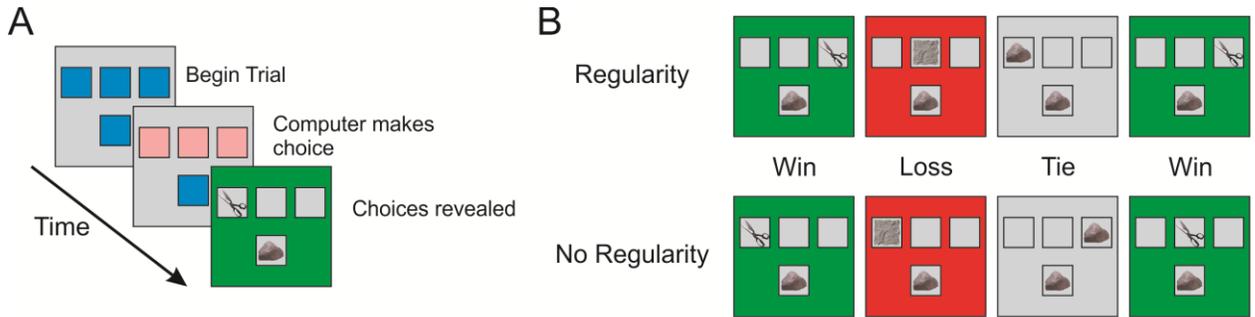
- 1) *Baseline*: 30 trials in which the computer chose each item uniformly (i.e., the computer chose each item with a 33% frequency). In this stage, the computer's choices appeared pseudo-randomly in one of the top three boxes in both conditions.

- 2) Initial stage: 60 trials in which the computer played 'rock' on 70% of the trials with 'paper' and 'scissors' played 15% each for the remaining trials.
- 3) Switch stage: 50 trials in which the computer played 'scissors' on 70% of the trials with 'rock' and 'paper' played 15% each on the remaining trials.

Each participant played all three stages without being made aware that the computer had switched strategies (Figure 1c).

**Figure 1.** (A) Time course of each trial. After 500ms, the top three squares would turn pink to indicate that the computer had made its choice and that participants could make their selection. Once participants made their choice, both choices were displayed for 1000ms with a green background for a win, red for a loss, and grey for a tie. (B) Participants were assigned to one of two conditions. In the *regularity* condition, the computer's choices would always appear in the same respective location (i.e., 'rock' would always appear in the top left square, 'paper' in the top middle, and 'scissors' in the top right). In the *no regularity* condition, the computer's choices were equally likely to appear in all three squares. (C) Participants were exposed to 3 experimental stages: a *baseline* stage, where the computer chose all three options uniformly for 30 trials, an *initial* stage, where the computer selected 'rock' 70% of the time for 60 trials, and a *switch* stage, where the computer selected 'scissors' was selected 70% of the time for 50 trials.

Figure 1



## 2.2 Results

Participant performance was measured using win rates (i.e., the ratio of wins compared to losses and ties), play of the optimal choice (i.e., the rate that a participant played the item that would beat the computer's biased item), and reaction times.

### *Baseline*

The baseline portion of the task was used to ensure that any changes in participant performance were not due to initial biases in their performance. Overall, participant win rates in this stage were not different from chance and there was no advantage for either condition when comparing win rates (Mean win rate: Regularity = 0.35, No Regularity = 0.31;  $t(37) = -1.624$ ,  $p = 0.113$ ) and reaction times (Mean reaction time: Regularity = 1.46 sec, No Regularity = 1.42 sec;  $t(37) = -0.195$ ,  $p = 0.846$ ). Participants played 'rock' slightly above chance (Mean 'rock' play = 0.36, chance = 0.33;  $t(38) = 2.122$ ,  $p < 0.05$ ) and tended to prefer this option over 'paper' and 'scissors' ( $F(2,76) = 2.900$ ,  $p = 0.061$ ,  $\eta^2_{\text{partial}} = 0.071$ ). However, given that the optimal choice in the Initial stage would have been to play 'paper', the tendency to choose 'rock' in the baseline stage would not provide any significant advantage when participants subsequently played against the initial bias of the computer opponent.

### *Initial stage*

The analysis of the experimental stages began by examining the participants' ability to learn and exploit the computer's biased strategy in the initial stage. If participants managed to learn the computer's play, their win rates and play of the optimal choice in this

stage should be above chance. As expected, participants performed above chance in the rate at which they played the optimal choice (Mean play of optimal choice = 0.46, chance = 0.33;  $t(37) = 5.390$ ,  $p < 0.001$ ) and the rate at which they won (Mean win rate = 0.40; chance = 0.33;  $t(37) = 3.932$ ,  $p < 0.001$ ).

### *Switch Stage*

The next analysis examined participants' ability to adjust to changes in the computer's bias by measuring their performance in the switch stage. If participants managed to successfully adapt their play to match changes in the computer's play, they would be expected to switch their item preference to match the computer's switch. Again, participants performed above chance in the rate at which they played the new optimal choice (Mean play of the optimal choice = 0.55, chance = 0.33;  $t(37) = 8.010$ ,  $p < 0.001$ ) and the rate at which they won (Mean win rate = 0.45, chance = 0.33;  $t(37) = 6.861$ ,  $p < 0.001$ ) in the switch phase. Participants played the optimal choice at a higher rate in the switch stage than in the initial stage (Mean play of the optimal choice: Initial = 0.46, Switch = 0.55;  $t(38) = -2.415$ ,  $p < 0.025$ ; Figure 2) while also experiencing higher win rates (Mean win rates: Initial = 0.40, Switch = 0.45;  $t(38) = -2.030$ ,  $p < 0.05$ )

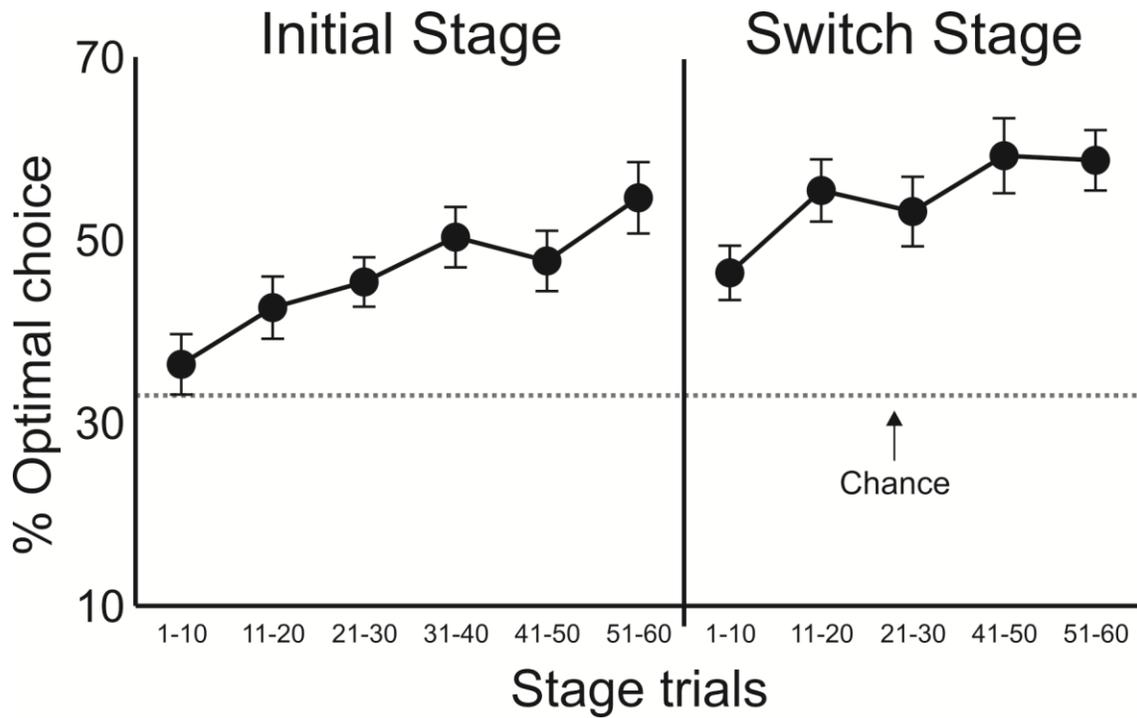
In order to assess how quickly participants started to switch their play to match the computer's strategies, participant plays were grouped over the course of the task into bins of 10 trials. The rate that participants played the optimal choice in each bin was compared to chance rates to determine at what point in each stage participants started preferring the optimal choice above chance. A one-sample t-test showed that participants tended to play the optimal choice above chance within the first 20 trials of the initial stage (mean = 0.43;

chance = 0.33;  $t(38) = 2.796$ ,  $p < 0.01$ ) and within the first 10 trials of the switch stage (mean = 0.46; chance = 0.33;  $t(38) = 4.511$ ,  $p < 0.001$ ; Figure 2)

The analysis also examined if participant performance continued to increase in the trials that followed the point at which they started to prefer the optimal choice in each stage. The initial stage contained 6 bins of 10 trials and the rate of optimal play in the remaining 4 bins that followed the participants' switch to favouring the optimal choice was examined. The switch stage contained 5 bins of 10 trials and the rate of optimal play in the 4 bins that followed preference for the optimal choice in this stage was also examined. A repeated measures ANOVA revealed that participants tended to increase their play of the optimal choice after preferring the optimal choice in the initial stage ( $F(3,114) = 3.056$ ,  $p < 0.035$ ,  $\eta^2_{\text{partial}} = 0.074$ ) but not in the switch stage ( $F(3,114) = 1.293$ ,  $p = 0.280$ ,  $\eta^2_{\text{partial}} = 0.033$ ; Figure 2), suggesting that participants reached ceiling in the rate that they played the optimal choice on the trials that followed their strategy switch.

**Figure 2**

**Figure 2.** Play of the optimal choice separated into bins of 10 trials over the course of the *initial* and *switch* stages. Overall, participants played the optimal choice at a higher rate in the *switch* stage than in the *initial* stage. Participants started to prefer the optimal choice at a rate above chance (indicated by the dotted line) within the first 20 trials of the *initial* stage and within the first 10 trials of the *switch* stage. Error bars represent one standard error of the mean.

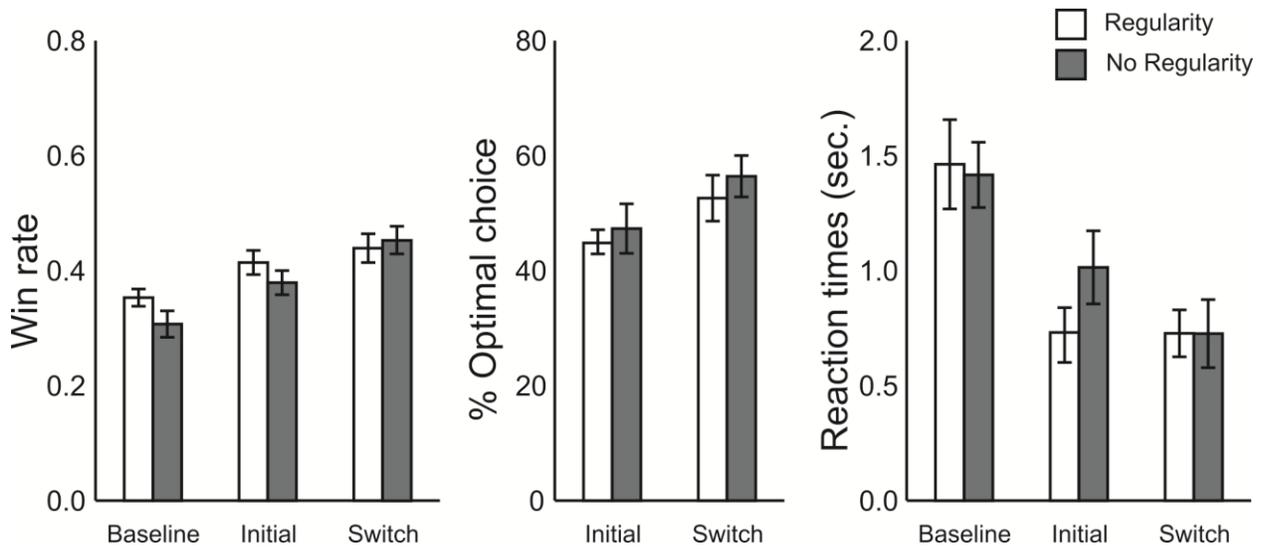


### *Examining the influence of spatial regularity*

Next, performance between both spatial regularity conditions was compared. If spatial regularities provide a learning advantage, higher win rates and higher rates of play of the optimal choice would be expected for participants in the regularity condition. The first analysis was to compare overall performance in the initial and switch stages between both conditions. An independent samples t-test did not yield any differences when comparing overall win rates (Mean win rates: Regularity = 0.43, No regularity = 0.42;  $t(37) = -0.444$ ,  $p = 0.660$ ) or play of the optimal choice (Mean play of the optimal choice: Regularity = 0.49, No regularity = 0.52;  $t(37) = 0.836$ ,  $p = 0.409$ ). Reaction times were nominally quicker in the regularity condition, but this difference did not reach significance (Mean reaction times: Regularity = 0.73 sec, No regularity = 0.87 sec;  $t(37) = 1.165$ ,  $p = .251$ ). When a comparison was made between conditions in each stage of the experiment, none of the differences were found to be significant (Figure 3).

**Figure 3**

**Figure 3.** Win rates, percent play of the optimal choice, and reaction times between the *regularity* and *no regularity* conditions. None of the differences were found to be significant. Error bars represent one standard error of the mean.



## 2.3 Discussion

The main goal of this first experiment was to explore the potential benefits of spatial regularity on our ability to detect regularities associated with non-spatial events. In both conditions, participants managed to exploit the computer strategies and switch their play in accordance with changes in the computer strategy. This demonstrates that participants managed to exploit the computer's bias and update their play choices when the information they receive from the game changed. However, despite being able to exploit the computer's bias, participants exposed to spatial regularities did not show additional benefits. These results suggest that although congruent spatial regularities may influence our ability to discriminate and respond to stimuli (Simon, 1969; Drucker & Anderson, 2010), they do not necessarily influence our ability to detect regularities associated with the stimuli.

The results of this experiment did not provide any definitive evidence to the effectiveness of spatial regularity; however this might be explained by the task being too simple. Participants tended to favour the optimal choice, and drop their play of the worst choice, within the first 20 trials of the initial strategy, and within the first 10 trials of the switch strategy. Additionally, after switching to the optimal choice in the switch strategy, play of the optimal choice hit ceiling, revealing no significant improvement after having learned the pattern in computer play. Given how quickly participants managed to notice the computer's bias, and that their maximum performance on the task was reached shortly thereafter, it is possible that the task itself may have been too easy for participants. If the task itself was easy, participants may have either had no need to make use of redundant spatial information or that the task's measures were too crude to detect it. If difficulty influences the effects of spatial regularities on learning, a more pronounced difference in

performance would be expected on difficult tasks. Experiment 2 was designed to measure the effects of spatial regularities when participants played against easy and difficult computer strategies.

## CHAPTER 3: Experiment 2

Experiment 2 was designed to explore the possibility that the difficulty in learning task contingencies could influence the manner in which spatial regularities are used to support or influence our ability to detect patterns in non-spatial events. If the results from Experiment 1 were due to the relative simplicity of the computer strategy, it was hypothesized that congruent spatial regularities would provide no advantages when participants were exposed to an easy computer strategy, but would assist participants when they were exposed to a more difficult strategy.

In addition to the effects of spatial regularity on learning, a strategy switch was included in the hard condition. If participants are aided by spatial regularity in the hard condition, it was hypothesized that these same regularities would improve the ability of participants to notice a change in their environment, and cause them to switch more quickly in accordance with changes in the computer's play strategy.

### 3.1 Methods

#### *Participants*

40 undergraduates (29 female, Mean age = 20.6 years, SD = 1.5 years) from the University of Waterloo participated in this experiment for course credit.

#### *RPS Game Environment*

The RPS game environment was identical to the game play in Experiment 1, with one minor exception. Some participants had indicated that the background color change when the trial results were displayed was uncomfortable to view. To remove this

discomfort, instead of changing the colour of the entire background, only the background of the computer and participant squares would change colors to indicate the result of the trial.

### *Experiment 2 trial set-up*

In order to measure the effects of difficulty on learning, participants were exposed to repeating sequences of computer play rather than different frequencies of play choices. Data from previous work using RPS has shown that participant performance can be difficult to distinguish from chance when the biased play choice is at only 50% (e.g., the computer chooses 'rock' 50% of the time with 'paper' and 'scissors' chosen 25% of the time each; Danckert et al., 2012). Sequences were chosen instead of probability distributions to make a clearer distinction between easy and difficult conditions, with the assumption that shorter sequences would be easier to learn than longer sequences (Figure 4a). After five practice RPS trials, participants were exposed to a set of easy sequences, then a set of hard sequences.

### *Easy condition trial set-up*

In the easy portion of the experiment, participants were exposed to two sequences that contained separate permutations of the list 'rock', 'paper', 'scissors'. Participants would play against the first sequence until they managed to beat the sequence two times in a row (i.e., 6 sequential wins), or until they reached 90 trials. Once finished, the participants were given a break before playing against the second easy sequence. The order in which the sequences were presented remained constant between participants. To measure the influence of spatial regularity on sequence learning, each of the two sequences were

presented with a different spatial association (either regularity or no regularity). The order in which the spatial regularity was presented was counterbalanced between participants (Figure 4b).

#### *Hard condition trial set-up*

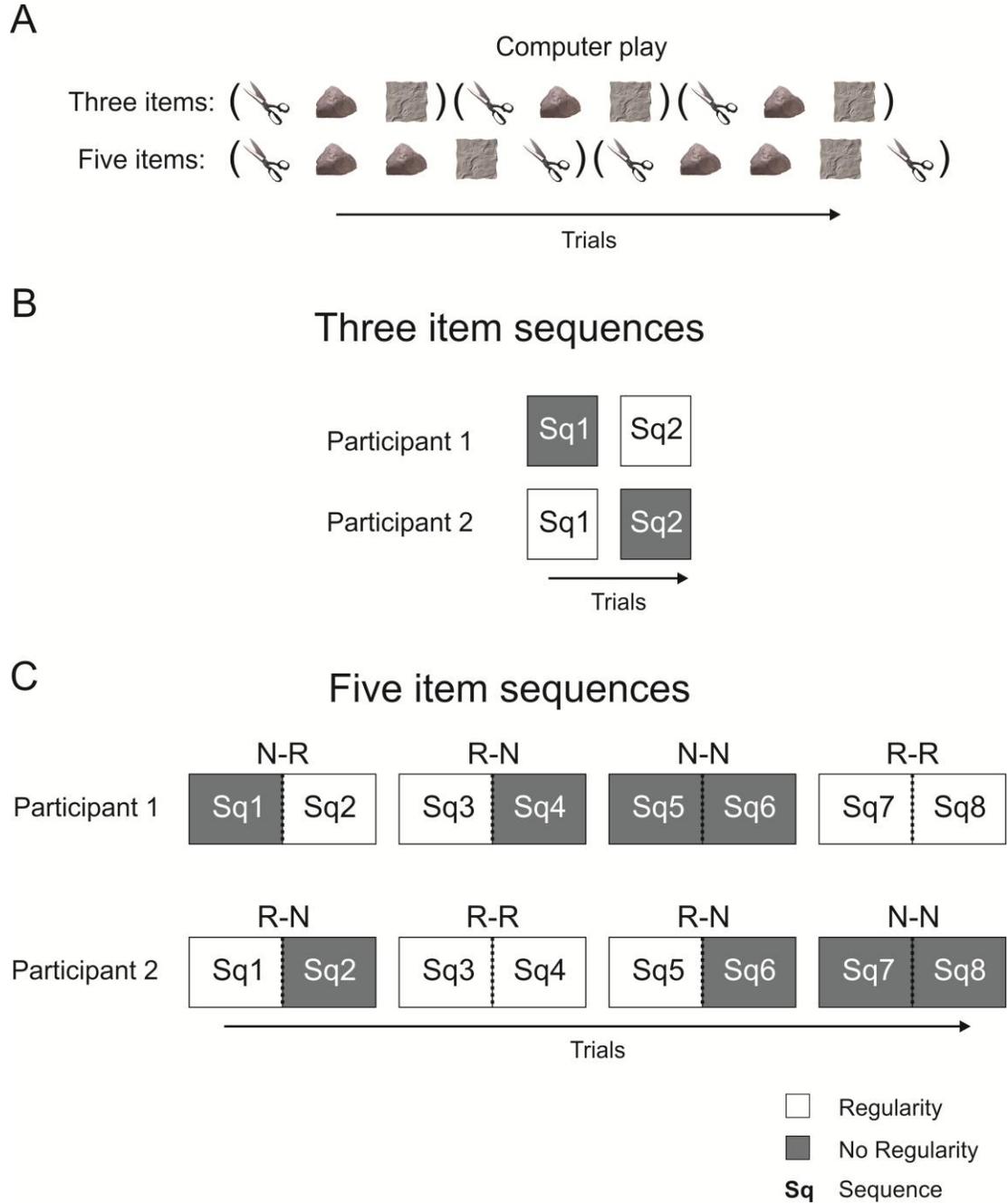
The hard condition was created to test the influence of spatial regularity on a task when it becomes more difficult. To make this task more difficult, the sequences in the hard condition contained five items. The sequences were built using two sets of the items 'rock', 'paper' and 'scissors' and randomly removing one of the six items. Each list of five items was pseudo-randomly shuffled using the Python language Random module and modified if necessary to ensure that they were distinct from each of the other sequences.

Given the number of available permutations with the setup of the hard sequences, this study had the opportunity to examine potential effects of spatial regularity when the computer's strategy changed, and when spatial regularity remained constant between strategies (as in Experiment 1) or changed between strategies (i.e., one strategy would be presented with regularity and one without regularity). To measure this, participants were exposed to four blocks of trials that each contained two sequences. Participants would start each block by playing against a first sequence until they had beaten it two times in a row (i.e., 10 sequential wins) or until they reached a maximum of 90 trials. The computer then switched to a second sequence without the participant being informed that the sequence had changed. The block finished once they beat the new sequence two times in a row or reached a maximum of 90 trials.

In the hard condition, participants were exposed to 4 blocks of trials, each containing a distinct switch in the spatial regularity of the sequences. One block contained two sequences with the same spatial regularity (R-R), a first sequence that contained spatial regularity and switched to a sequence with no regularity (R-N), a first sequence that contained no regularity and switched to a sequence with regularity (N-R), and two sequences that did not contain any spatial regularity (N-N). In the sequences that contained spatial regularities, 'rock' was always presented in the top left, 'paper' always displayed in the top middle, and 'scissors' was always displayed in the top right. To account for order effects, participants were exposed to the blocks of sequences in the same order, but the spatial regularity switch in each block was counterbalanced using a balanced latin squares design (Figure 4c).

**Figure 4.** (A) Participants in Experiment 2 played RPS against a computer that repeated sequences of plays. The sequences each contained three items in the easy condition and five items in the hard condition. Participants were exposed to each sequence until they could either beat it two times in a row (i.e., 6 consecutive wins in the easy condition and 10 consecutive wins in the hard condition). (B) Participants were each exposed to two blocks of easy sequences, one with spatial regularity and one with no spatial regularity. The order of the blocks remained constant for each participant, but spatial regularity was counterbalanced between participants. (C) In the hard condition, participants were exposed to four blocks of trials, each containing two sequences. In each block, participants played against a first sequence and were then switched to a second sequence without being made explicitly aware that a switch had occurred. The sequences were presented either with a spatial regularity (R) or no spatial regularity (N). The block order remained constant for each participant, but the spatial regularity of each block was counterbalanced between participants using a balanced latin squares design.

Figure 4



## 3.2 Results

### *Sequences of three vs. sequences of five*

To determine whether the sequences of five items were in fact more difficult than sequences of three items, performance in each part of the experiment was compared. Participants took half as long on average to learn sequences with three items (Mean trials to criterion: three items = 26.63, five items = 56.36;  $t(37) = -8.992$ ,  $p < 0.001$ ) and had higher overall win rates (Mean win rates: three items = 0.59, five items = 0.53;  $t(37) = 2.786$ ,  $p < 0.01$ ). It is possible that participants took more trials to learn sequences of five because the sequences themselves contained more items (i.e., if a participant only needs to be exposed to a sequence once to learn it, it would take them 3 trials to learn a sequence of three items and 5 trials to learn a sequence of five items). To account for this possibility, the mean number of iterations participants required to learn each sequence length was compared. Participants required exposure to fewer iterations to learn the sequence of three items (Mean number of iterations: three items = 9.16, five items = 11.54;  $t(37) = -2.458$ ,  $p < 0.02$ ), confirming that the sequences of five items were harder to learn than sequences of three items.

### *Easy sequences*

Based on the results from Experiment 1, spatial regularity was not expected to improve participant performance when learning easy sequences. However, participants tended to take fewer trials to learn sequences with a spatial regularity, a difference that approached significance (Mean trials to criterion: Regularity = 22.24 trials, No regularity = 31.03;  $t(37) = -1.825$ ,  $p = 0.076$ ; Figure 6a). A nominal difference was found when

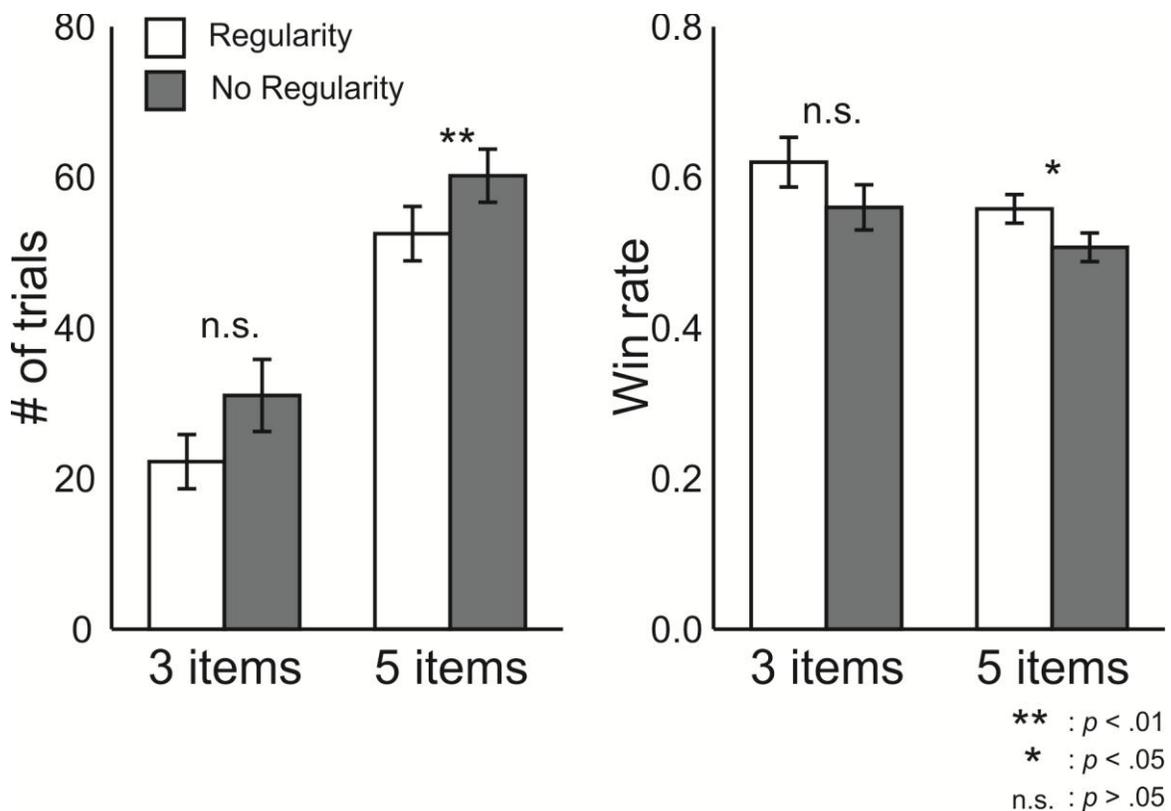
comparing win rates (Mean win rates: Regularity = 0.615, No regularity = 0.563;  $t(37) = 1.276$ ,  $p = 0.210$ ; Figure 6b) and reaction times (Mean reaction times: Regularity = 1.19 sec, No regularity = 1.32 sec;  $t(37) = -1.060$ ,  $p = 0.296$ ), but none of these differences were significant (Fig 5).

### *Hard sequences*

It was hypothesized that spatial regularities would improve performance when the task itself increased in difficulty. An analysis of the hard condition began by dividing performance on all hard sequences based on the presence of a spatial regularity. Overall, participants took fewer trials to learn sequences presented with a spatial regularity (Mean trials to criterion: Regularity = 52.51, No regularity = 60.20;  $t(37) = -3.771$ ,  $p = 0.001$ ) and had higher win rates (Mean win rates: Regularity = 0.56, No regularity = 0.51;  $t(37) = 3.070$ ,  $p < 0.005$ ; Figure 5). Participant reaction times were nominally quicker in the regularity condition, but this difference was not significant (Mean reaction times: Regularity = 1.05 sec, No regularity = 1.12 sec;  $t(37) = -1.118$ ,  $p = 0.271$ ).

**Figure 5**

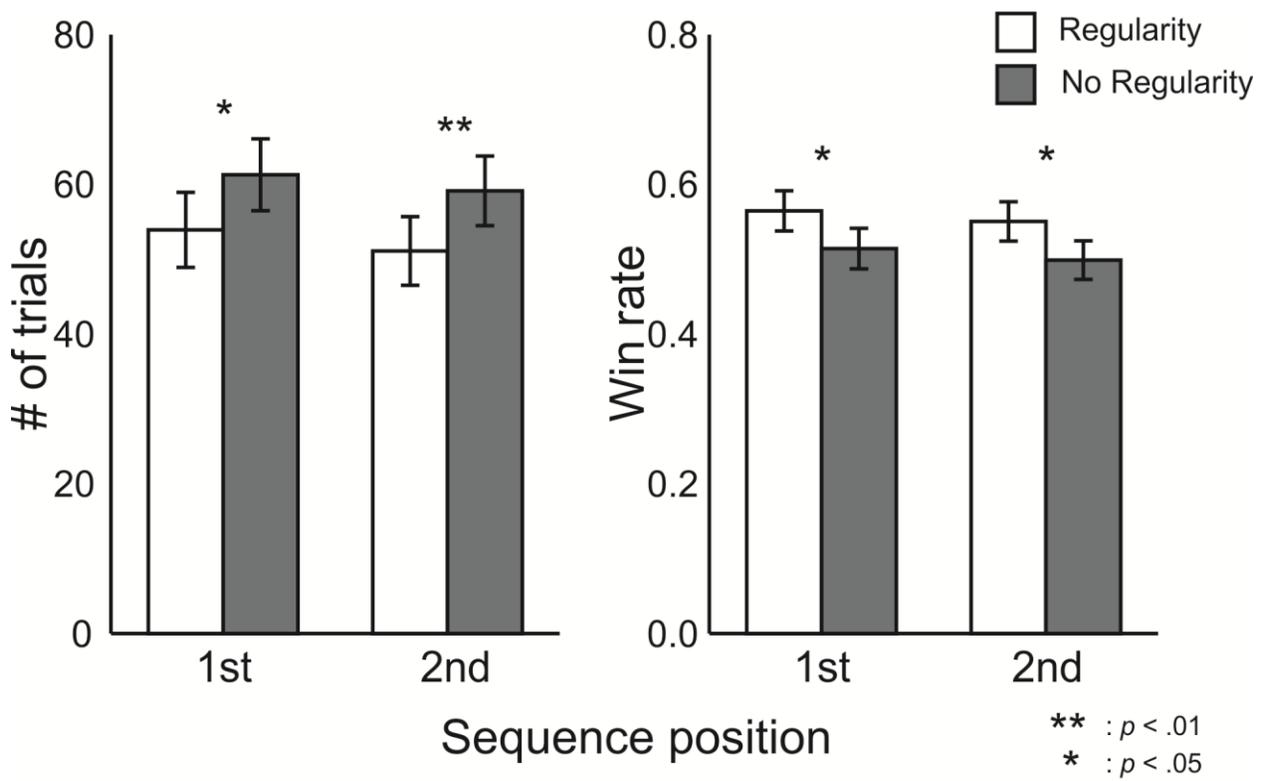
**Figure 5.** Participant performance when playing against repeating sequences of three computer plays (3 items) or five computer plays (5 items). The number of trials required to learn each sequence along with win rates tended to be lower when a spatial regularity was present in sequences of 3 items, although the differences were not significant. While playing against sequences of 5 items, participants took fewer trials to learn each sequence and experiences higher win rates when spatial regularities were present. Error bars represent one standard error of the mean.



The hard sequences were then split into groups based on their position in each block to measure the effects of spatial regularity on learning and detecting strategy changes. Using paired samples t-tests, regularity was found to decrease the number of trials required by participants to learn both the first sequence (Mean trials to criterion – first sequence: Regularity = 53.92, No regularity = 61.28;  $t(37) = -2.163$ ,  $p < 0.04$ ) and the second sequence (Mean trials to criterion – second sequence: Regularity = 51.11, No regularity = 59.13;  $t(37) = -3.121$ ,  $p < 0.004$ ) in each block. Participants also experienced higher wins when a spatial regularity was present in both the first sequence (Mean win rates – first sequence: Regularity = 0.56, No regularity = 0.51;  $t(37) = 2.305$ ,  $p < 0.03$ ) and second sequence (Mean win rates – second sequence: Regularity = 0.55, No regularity = 0.50;  $t(37) = 2.443$ ,  $p < 0.02$ ; Figure 6).

**Figure 6**

**Figure 6.** Participant performance on sequences of five items split by the sequence's position in each block. Participants took fewer trials to learn sequences and experienced higher win rates when a spatial regularity was present, regardless of the sequence's position in the block. Error bars represent one standard error of the mean.

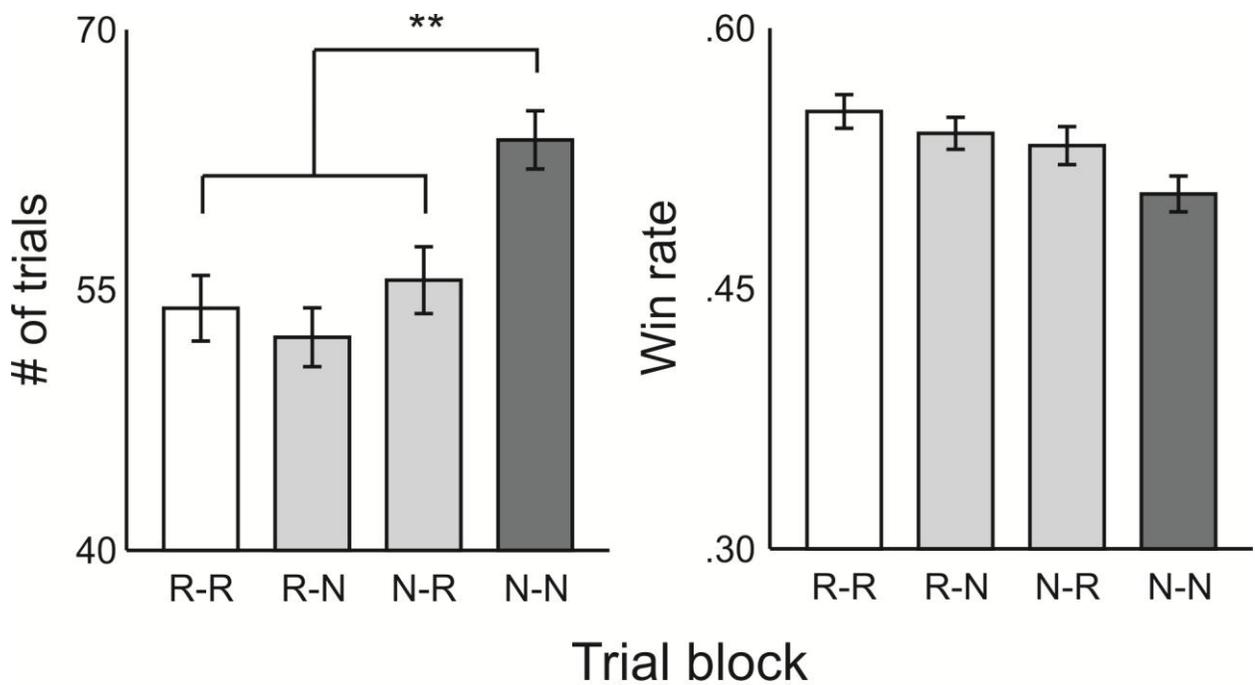


### *Spatial regularity switches in the hard blocks*

Experiment 2 was also interested in the examining the ability to adapt one's play strategy in the face of changes to the computer opponent's play when the regularity of the hard sequences varied within each block. Performance was expected to be best overall in the R-R blocks, equal in the R-N and N-R blocks, and poorest in the N-N blocks. A repeated measures ANOVA comparing the average trials required to learn each sequence in the four different blocks revealed a main effect for block ( $F(3,111) = 3.214, p < 0.03, \eta^2_{\text{partial}} = 0.080$ ), confirming that performance was not homogenous across all blocks. When each block was compared using a Helmert simple effects contrast, participants required significantly more trials to learn the sequences in the N-N block compared to all other blocks (Mean trials to criterion: R-R = 53.95, R-N = 52.28, N-R = 55.57, N-N = 63.64;  $F(1,37) = 8.125, p < 0.01, \eta^2_{\text{partial}} = 0.180$ ). The same contrast did not reveal any further differences between the other blocks ( $F(1,37) = .520, p = 0.475, \eta^2_{\text{partial}} = 0.014$ ). Participants also tended to have the highest win rates in the R-R block, similar win rates in the R-N and N-R blocks, and lowest win rates in the N-N group, but a repeated measures ANOVA comparing the win rates in each block was not significant ( $F(3,111) = 1.174, p = 0.323, \eta^2_{\text{partial}} = 0.031$ ; Figure 7).

**Figure 7**

**Figure 7.** Average performance in each block according to spatial arrangement. When participants were exposed to two sequences with no spatial regularity (N-N), they took a higher number of trials to learn each sequence when compared to the blocks that contained at least one sequence with spatial regularity (R-R, R-N, and N-R). Although mean win rates were also nominally higher when a spatial regularity was present in at least one block sequence, the trend was not significant. Error bars represent one standard error of the mean.



\*\* :  $p < .01$

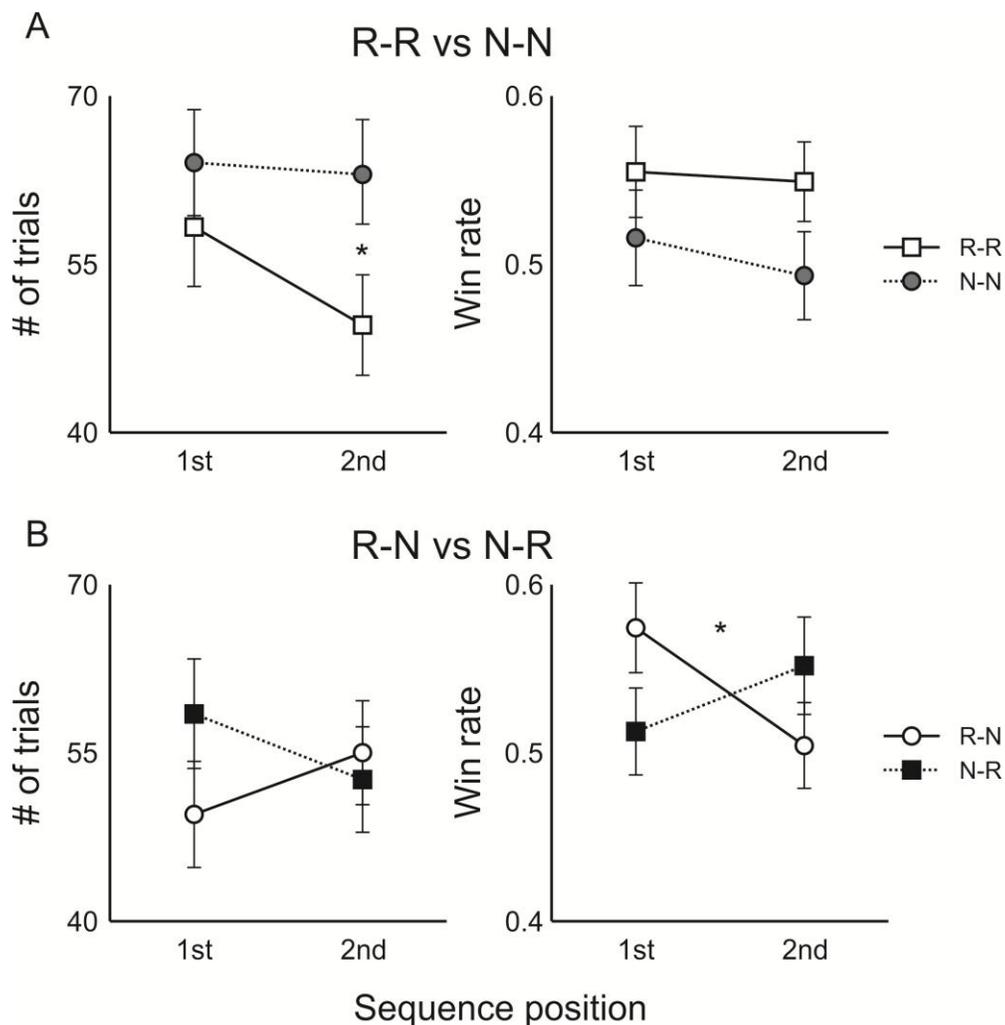
Since performance differed between the four blocks, each sequence of the different blocks was examined in more detail. The analysis began by comparing the performance in the R-R and N-N blocks. If spatial regularities aid sequence learning, higher performance would be expected in the first and second sequences of the R-R block when compared to the N-N block. Participants took nominally fewer trials to learn the first sequence in the R-R blocks (Mean trials to criterion: R-R = 58.31, N-N = 64.05) and experienced a nominally higher win rate (Mean win rates: R-R = 0.55, N-N = 0.52) but a paired samples t-test did not find either of these differences to be significant (Trials to criterion:  $t(37) = -1.145$ ,  $p = 0.260$ ; Win rate:  $t(37) = 1.328$ ,  $p = 0.192$ ). When the second sequences in both blocks were compared, participants required fewer trials to finish the second sequence in the R-R block than in the N-N block (R-R = 49.58, N-N = 63.24;  $t(37) = -2.523$ ,  $p < 0.02$ ) and tended to experience a higher win rate (R-R = 0.55, N-N = 0.49;  $t(37) = 1.776$ ,  $p = 0.08$ ). Participants also improved their performance from the first to the second sequence in the R-R block (Trials to criterion – R-R block: First sequence = 58.31, Second sequence = 49.58;  $t(37) = 2.034$ ,  $p < 0.05$ ), but showed no improvement in the N-N block (Trials to criterion – N-N block: First Sequence = 64.05, Second sequence = 63.24;  $t(37) = 0.157$ ,  $p = 0.876$ ; Figure 8a).

Participant performance was then compared in blocks where spatial regularity changed between the block sequences. Performance was expected to be best on sequences that contained a spatial regularity, regardless of their position in the block. When the sequences were divided in the R-N and N-R blocks by regularity, a paired samples t-test confirmed that participants tended to take fewer trials when a regularity was present (Trials to criterion: Sequences with regularity = 51.08, Sequences with no regularity =

56.76;  $t(37) = -1.943$ ,  $p = 0.06$ ) and experienced higher win rates (Win rates: Sequences with regularity = 0.56, Sequences with no regularity = 0.51;  $t(37) = 3.159$ ,  $p < 0.004$ ). A 2x2 repeated measures ANOVA with block (R-N, N-R) and sequence position (first sequence, second sequence) as within subject factors found a trending block by sequence interaction when trials were used as a dependent variable ( $F(1,37) = 3.776$ ,  $p = 0.06$ ,  $\eta^2_{partial} = 0.093$ ), and a significant interaction for win rates ( $F(1,37) = 9.977$ ,  $p < 0.004$ ,  $\eta^2_{partial} = 0.212$ ; Figure 8b). This confirms that performance tended to be better on sequences that contained a regularity, regardless of the regularity's position in the block.

**Figure 8**

**Figure 8. (A)** Performance comparison between the R-R and N-N blocks. Participants took nominally fewer trials to learn the first sequence of each block and significantly fewer trials to learn the second sequence. They also experienced nominally higher win rates in the R-R block, but this difference did not reach significance. **(B)** Performance comparison between the R-N and N-R blocks. Participants took fewer trials to learn a sequence, and experienced higher win rates, when the sequence was resented with a spatial regularity, regardless of the sequence's position within a block. Error bars represent one standard error of the mean.



### 3.3 Discussion

Although spatial regularity did not seem to affect performance in Experiment 1, the seeming ease with which participants managed to learn computer strategies led us to hypothesise that the main task may have been too simple for participants and that the additional information provided by spatial regularities was not necessary to help them predict the computer's next play. In Experiment 2, participants played against easy and hard sequences of RPS play with varying spatial regularities.

Although a consistent nominal advantage for spatial regularity was present in the easy sequences, none of the differences in performance were significant. This suggests that spatial regularities may still potentially help with the learning of easier sequences, but that the task may not have been sensitive enough to measure a significant difference.

In the hard condition, participants were exposed to repeating sequences of five RPS items. A comparison in performance between the easy and hard conditions confirmed that the sequences containing five items were harder to learn than sequences of three items. When performance was compared between the hard sequences that contained a spatial regularity and those that did not, participants were found to required fewer trials to learn sequences and managed higher win rates when a spatial regularity was present.

Next, the different blocks of hard trials were examined to explore the influence of spatial regularity on learning and detecting changes in the computer's play. Overall, performance on the first and second sequences in each block was improved by spatial regularities. When the spatial regularity remained consistent between the two sequences in each block, learning of the initial sequence was slightly improved and performance on the second sequence was significantly improved. When the spatial regularity switched between

sequences within each block, learning and switch detection were both improved by the presence of spatial regularity, regardless of the position of the sequence containing the spatial regularity.

Overall, these results confirm that spatial regularities can improve learning, and can help us detect unexpected changes in our environment. However, it seems that these benefits present themselves when the primary task itself is difficult.

## CHAPTER 4: General Discussion

The purpose of this research was to provide insight into the influence of redundant spatial features on our ability to detect regularities in our environment. This study demonstrated that spatial regularities can facilitate the integration of regularities associated with non-spatial events, and that their effect may be more pronounced when the regularities of non-spatial events are more difficult to interpret. These results suggest that in addition to helping humans respond (Simon, 1969) and discriminate (Druker & Anderson, 2010) between different events, spatial regularities can also assist in learning the statistical properties of those events.

One potential limitation to this interpretation of these results is the absence of a neutral condition, where the computer's choices would always appear in the same fixed screen location. A neutral condition was omitted to avoid overtly signalling to participants a change in the task (particularly in Experiment 2). However, without a neutral condition for comparison, we cannot directly assert whether spatial *regularity improves* learning or whether spatial *irregularity interferes* with learning. Future studies comparing both the regularity and no regularity conditions with a neutral condition would provide additional insight into the direction of this influence.

These findings are potentially relevant to research exploring the broader topic of mental model building and updating (Danckert et al., 2012; Gläscher, Daw, Dayan, & O'Doherty, 2010; Daw, Gershman, Dayan, & Dolan, 2011; Tenenbaum, Kemp, Griffiths, & Goodman, 2011; Lauwereyns, 2010). Research exploring mental models has focused on understanding the way humans use prior experiences to explain and predict future events. This work has also explored our ability to update mental models when the events in the

environment no longer match the predictions derived from our current model. The results from Experiment 2 suggest that spatial regularities can improve our ability to learn the properties of non-spatial events, and facilitate our ability to adapt our behaviour when the environment changes. This suggest that in addition to helping us build representative models of our environment, spatial regularities can also help us detect mismatches between our models and the environment, and update them accordingly.

Research into the brain activation involved with processing redundant stimulus features provides a possible neurological account for the learning benefit of spatial regularities. Fias and colleagues (2001) tested the degree to which the processing of a task-*relevant* feature would be influenced by task-*irrelevant* features. They found that task-*irrelevant* features influenced participant responses to task-*relevant* features when these features shared common regions of neural activation, but not in cases when the task-*relevant* features activated separate neural regions (Fias et al., 2001). In the context of the current experiment, the neural regions likely involved in processing the spatial features of the stimuli may also be involved in learning patterns and sequences. Research has implicated regions of the posterior parietal cortex in spatial attention (Colby & Golberg, 1999; Mesulam, 1999; Silver, Ress, & Heeger, 2005) and sequence learning (Sakai et al., 1998; Jenkins et al., 1994). It is possible that the benefits observed in Experiment 2 could be due to overlapping regions of neural activation which served to strengthen a participant's ability to perceive patterns presented with spatially redundant features. Future studies using non-spatial redundant features (e.g., color, shape, luminosity) could test this relationship more closely to determine the extent to which overlapping regions of

neural activation associated with multiple features of a stimulus could influence our ability to detect regularities in our environment.

The current study has demonstrated that our ability to predict events can be influenced by features not immediately related to the events themselves. This research provides an insight into the way we process information, and proposes that we cannot discount the influence of redundant features when studying the mechanisms involved in learning. It also provides some evidence for the interconnectedness of different brain regions, and how they may interact to facilitate different areas of cognition.

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